Chapter 6

Discussion and Conclusion

In the large-scale outdoor experiment, the result of the accumulated log likelihood (Fig. 5.1) shows a large gap between the accumulated log likelihood of each ST-SLAM (even with 10,000 particles) and that of true-move-only SLAM. This gap indicates that there is still room for improvement in terms of total performance of ST-SLAM. To achieve better SLAM performance, one possible approach is using improved proposal distributions that better approximate the target full joint posterior. In [1], an improved proposal distribution (FastSLAM 2.0) that takes sensor measurements into account is introduced to achieve more effective particle sampling when the accuracy of odometry is low relative to the accuracy of sensor measurements. In [7], an even more effective proposal distribution is discussed as a variant of the FastSLAM 2.0 proposal distribution. The other approach to improving ST-SLAM would be combining different geometric landmarks such as 3D line segments. Lines are more useful than points to estimate the orientation of a robot. Achieving loop-closure in the large-scale environment would be the first step. We expect that using more distinctive landmarks helps a successful loop-closure.

In this research, we have demonstrated the feasibility of ST-SLAM through two distinct experiments: a large-scale simulated-outdoor experiment and a real-indoor experiment. Although ST-SLAM performed satisfactorily under the environments with different modes of difficulty, it is not obvious that ST-SLAM is really capable of achieving successful SLAM in large-scale environments in the real world. Therefore, we need to conduct large-scale ST-SLAM experiment in a real outdoor environment in the future.

We have empirically shown that our light-weight 3D point sensor based on Shi-Tomasi image points works robustly enough for supplying the FastSLAM algorithm with accurate measurement data. However, it is desired that we determine how accurate our sensor measurements are relative to the sensor models that are based on image point features with more informative descriptors such as SIFT. Therefore direct comparisons with SIFT-based 3D point sensor is strongly expected in the future.

In ST-SLAM experiments, we have used a 3.0 GHz desktop PC with 3 GB RAM. We find that ST-SLAM requires 1.5 GB memory consumption at best (in case of ST-SLAM with 10,000 particles). So far, our ST-SLAM implementation in C runs in real time (faster than 1 Hz) when the number of particles is less than 100. However, ST-SLAM with 1,000 and 10,000 particles run approximately at 1/30 Hz and 1/60 Hz, respectively, which is far below real-time performance. Given that ST-SLAM demonstrates its remarkable performance when running with more than 1,000 particles, we need further optimization of the ST-SLAM source code to make it a real-time system in practical situations. We should also pursue a method of more efficiently handling large number of landmarks in database, since we observe the slowdown of the system when the stored landmarks scale to more than several thousands.

Here we summarize recommended future work that will bring ever promising results on top of this research.

- Introduce more elaborate proposal distributions.
- Combine new geometric landmarks (e.g. line segments) with existing 3D point landmarks.
- Conduct large-scale ST-SLAM experiments in outdoor environments.
- Directly compare the Shi-Tomasi-feature-based sensor and SIFT-based sensors.
- Optimize ST-SLAM code to achieve real-time performance.

In this research, we have introduced a cost-effective and computationally lightweight visual sensor model that collaborates well with the Rao-Blackwellized particle filter. The combination of trinocular stereo and Shi-Tomasi point features makes it possible to efficiently extract 3D point landmarks in environments that are accurate enough for input to FastSLAM.

The simulated-outdoor and real-indoor experiments demonstrate successful localization and mapping using our ST-SLAM algorithm. In the large-scale simulated-outdoor experiment, ST-SLAM demonstrates its capability of globally localizing a robot in a large-scale environment and consistently mapping thousands of 3D point landmarks in the environment. We also find that accurate yaw estimation, rather than horizontal Euclidean moves, is crucial to successful robot localization. In the real-indoor experiment, ST-SLAM proves its robustness to image noise, camera calibration error, and odometry error. ST-SLAM performs significantly better than odometry-only SLAM under typical odometry noise levels. Combining the results of the two experiments, we conclude that ST-SLAM is feasible as a lightweight alternative to RBPF methods using sensors based on rich, computationally expensive feature descriptors such as SIFT.